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Soil quality assessment for desertification based on multi-indicators with the best-worst method in a semi-arid ecosystem

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Abstract: Since there are some signs of land degradation and desertification showing how soil sustainability is threatened, it is crucial to create a soil quality index (SQI) model in the semi-arid Çorum Basin, situated between the Black Sea and Anatolia Region, Central Turkey. The primary aims of the study are: (1) to determine SQI values of the micro-basin in terms of land degradation and desertification. Moreover, the best-worst method (BWM) was used to determine the weighting score for each parameter; (2) to produce the soils' spatial distribution by utilizing different geostatistical models and GIS (geographic information system) techniques; and (3) to validate the obtained SQI values with biomass reflectance values. Therefore, the relationship of RE-OSAVI (red-edge optimized soil-adjusted vegetation index) and NDVI (normalized difference vegetation index) generated from Sentinel-2A satellite images at different time series with soil quality was examined. Results showed that SQI values were high in the areas that had almost a flat and slight slope. Moreover, the areas with high clay content and thick soil depth did not have salinity problems, and were generally distributed in the middle parts of the basin. However, the areas with a high slope, poor vegetation, high sand content, and low water holding capacity had low SQI values. Furthermore, a statistically high positive correlation of RE-OSAVI and NDVI indices with soil quality was found, and NDVI had the highest correlative value for June (R^2=0.802) compared with RE-OSAVI.

Keywords: soil quality; land degradation; desertification; best-worst method; remote sensing

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1 Introduction

Soil is among the most crucial natural resources for human, flora, and fauna in terrestrial ecosystems. Soil is necessary to meet the demands of the world's population, which increases every year, to maintain its quality, agricultural productivity, and food security (Hatfield, 2014). Therefore, it is crucial to know soil quality for its sustainability, and the measures that can be taken later with the increasing pressures and demands of the world's population on the soil. Researchers described soil quality as the soil's capacity to function based on assessing its physical, chemical, and biological properties (Veum et al., 2014). It is well known that the productive function of the soil, i.e., its quality, decreases with the increased negative pressure on the soil. As noted by many researchers, soil quality has decreased due to land degradation and desertification

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in several ecosystems of the world because of human activities, such as unconscious and excessive consumption of natural resources, deforestation, soil erosion, and overgrazing (Lal et al., 2003; Qasim et al., 2017; Demirağ Turan et al., 2019; Zeraatpisheh et al., 2020; Karaca et al., 2021). Soil degradation seriously threatens agricultural productivity, economic development, and long-term environmental health (Girmay et al., 2008; Zeraatpisheh et al., 2020). Undoubtedly, Turkey also suffers from soil degradation and a decline in soil productivity, which causes high rates of land degradation and serious consequences leading to desertification. In their study conducted on desertification in Turkey using 48 indicators and 37 sub-indicators, Türkeş et al. (2020) found that 12.7% of the lands in Turkey were in the low-risk class, 53.2% in the medium-risk class, and 25.5% in the high-risk class. Furthermore, regarding soil quality, 32.2% of the soils in Turkey were categorized as low to very low standards (Uzuner and Dengiz, 2020). Hence, a wide range of qualitative and quantitative soil quality index (SQI) studies have been carried out to detect soil productive capacity (Raiesi, 2017; Demirağ Turan et al., 2019; Santos-Francés et al., 2019; Karaca et al., 2021; Kaya et al., 2022).

As a crucial gauge of the health of plants and other living things in terrestrial ecosystems, SQI comprehensively evaluates the chemical, physical, and biological aspects of the soil (Doran et al., 1994; Karlen et al., 1997; Zeraatpisheh et al., 2020). Vegetation cover and its changes, which have significant direct and indirect effects on soil formation and impact soil properties, and a negative change in vegetation cover disrupts soil management, causing the soil to be adversely affected (Li et al., 2019). Taghipour et al. (2022) stated that SQI value decreased significantly with the change in vegetation density, especially in forests, pastures, and agricultural lands. In this regard, it is important that the soil properties change significantly in different vegetation types so that the soil quality also changes. Therefore, researchers have indicated that determining the chemical, physical, and biological characteristics of soils distributed in areas with various land uses and land covers is crucial for the best land management practices (Yifru and Taye, 2011; Ganiyu, 2018; Tauqeer et al., 2022a, b; Zhang et al., 2022).

Numerous investigations have revealed the significance of vegetation indices and satellite image data in determining soil quality. For example, Taghipour et al. (2022) concluded that SQI was highly correlated with vegetation distribution and the activity of soil organisms. Furthermore, Gen et al. (2021) integrated vegetation productivity models with vapor pressure deficit, minimum temperature, and soil quality into a simple water-temperature-soil index (WTSI), correlated soil quality with the normalized difference vegetation index (NDVI), and found high correlations with NDVI. However, some previous studies have demonstrated that the effects on soil properties differ with different vegetation types. Zhang et al. (2021) studied the impacts of various vegetation-land use types (forest, shrub, pasture, and agricultural lands) on soil quality in the subtropical Karst region of southwestern China. In the study, soil quality was calculated with the minimum dataset in addition to the total dataset using principal component analysis and factor analysis. Both methods found that the highest SQI values occurred in forest lands, followed by shrub and pasture lands, and the lowest SQI values in agricultural lands. Mirghaed and Souri (2022) also calculated SQI value separately with the total and minimum datasets and analyzed the relationship of land use, slope, elevation, and NDVI with soil quality. Result showed that soil quality was higher in forest lands than in agricultural and pasture lands. And significant relationships of soil quality with slope, elevation, and NDVI were found.

Misappropriate land use and management, soil erosion, changes in land use, topographic variation, degraded vegetation, and environmental pollutants negatively affect soil quality by altering its physical and chemical properties (Nosrati and Collins, 2019; Fathizad et al., 2020; Tian et al., 2020; Mamehpour et al., 2021). Therefore, it is important to consider soil quality for agricultural production, biodiversity conservation, reducing land degradation, and increasing economic prosperity (Tian et al., 2020). Da Rocha Junior et al. (2020) investigated the impact of various land uses and land cover changes on soil quality and soil ecosystem services. According to the research results, the conversion of forest lands into pasture and then into coffee farming led to reduced soil quality and decreased the ability of environmental services. According to Wen et al.

(2021), changes in plant restoration have a major impact on soil properties, as evidenced by significant differences in the soil physical-chemical properties on eight distinct vegetation restoration sites. Additionally, replanted shrubland and arboreal areas had slightly higher SQI values than the erosion-prone gully areas. Moreover, Derakhshan-Babaei et al. (2021) studied soil quality and examined the relationship of soil quality with erosion, geomorphology, and land use. They found that soil quality was higher in pastures than in agricultural lands, and higher in agricultural lands than in settlements. The researchers also noted that soil quality and erosion varied significantly in areas with a rough and steep topography.

Nowadays, many spectral indices, e.g., NDVI, red-edge modified chlorophyll absorption in reflectance index, leaf area index, green normalized difference vegetation, RE-OSAVI, and healthy index have been developed to analyze the bio-physical characteristics of plants (Fitzgerald et al., 2010; Bagheri et al., 2012; Wójtowicz et al., 2016). Vegetation types indicated by different indices can cause significant differences in the physical, chemical, and biological properties of the soil (Yifru and Taye, 2011; Tauqeer et al., 2022a). Therefore, physical, chemical, and biological changes in the soil also cause changes in soil quality (Liu et al., 2004). Hence, the relationships between soil quality and vegetation cover have been determined (Wen et al., 2021; Zhang et al., 2021; Taghipour et al., 2022; Zhang et al., 2022).

It is essential to utilize the soil's inherent and dynamic properties, including soil organic matter (SOM) content, pH, texture, and $CaCO_3$ concentration, to study their impacts on soil function and its spatial distribution in terms of land degradation and desertification, although numerous studies of soil quality have been done. The aims of the present study are: (1) to determine SQI values and the soils' spatial distribution in the semi-arid Çorum Basin with desertification and land degradation; and (2) to validate the biomass reflectance values of the obtained SQI values by investigating the correlation of RE-OSAVI and NDVI values produced from various time series of Sentinel-2A satellite imagery with soil quality.

2 Materials and methods

2.1 Study area

The study area is located between the Black Sea and Anatolia Region, Central Turkey with a total area about 660 km^2 (40°15′26″–40°32′09″N, 34°30′33″–35°08′08″E; Fig. 1). The elevation of the study area ranges from 683 to 1589 m a.s.l. A slightly flat slope (0%–2%) are located in the eastern basin. As for the distribution of aspect, the north-western parts of the basin usually have a southeastern aspect, while the areas located in the north-eastern and southeastern parts have southeastern and southwestern aspects (Fig. 2).

According to the data from the Çorum meteorological station, the annual average temperature is 10.8°C, and mean annual precipitation is 430.4 mm during 1929–2021. According to the De Mortanne's classification, the study area belongs to the semi-arid climate (Bölük, 2016). Brown forest soils are common in the study area. These soils cause the pedogenic calcification process due to the accumulation of secondary calcium carbonate with a low precipitation. Reddish-brown, alluvial, and kolluvial soils have the lowest distribution. Especially alluvial and kolluvial soils have no pedogenic horizon, and are formed on deposit material, so they can be called young soils. Furthermore, the majority of the soils in the basin are classified as cambisol, calcisol, fulvisol, and regosol by the world reference base for soil resources classification (Dengiz et al., 2017). According to Corine (2018), non-irrigated arable land occupies the largest area (28.3%; Table 1), follows by permanently irrigated arable land with an area of 97 km^2 (14.7%; Fig. 3).

The basin's geological structure was obtained from the General Directorate of the Mineral Research and Exploration (Akbaş et al., 2011). The oldest formation is the metamorphic rocks of the Permian-Triassic age in the northeastern part (Fig. 3). These metamorphic rocks cover an area of 22 km^2. The Quaternary terrain is observed along the river basin in the central part and constitutes an area of 135 km^2. Moreover, ophiolitic rocks occupy the largest part with an area of 192 km^2.

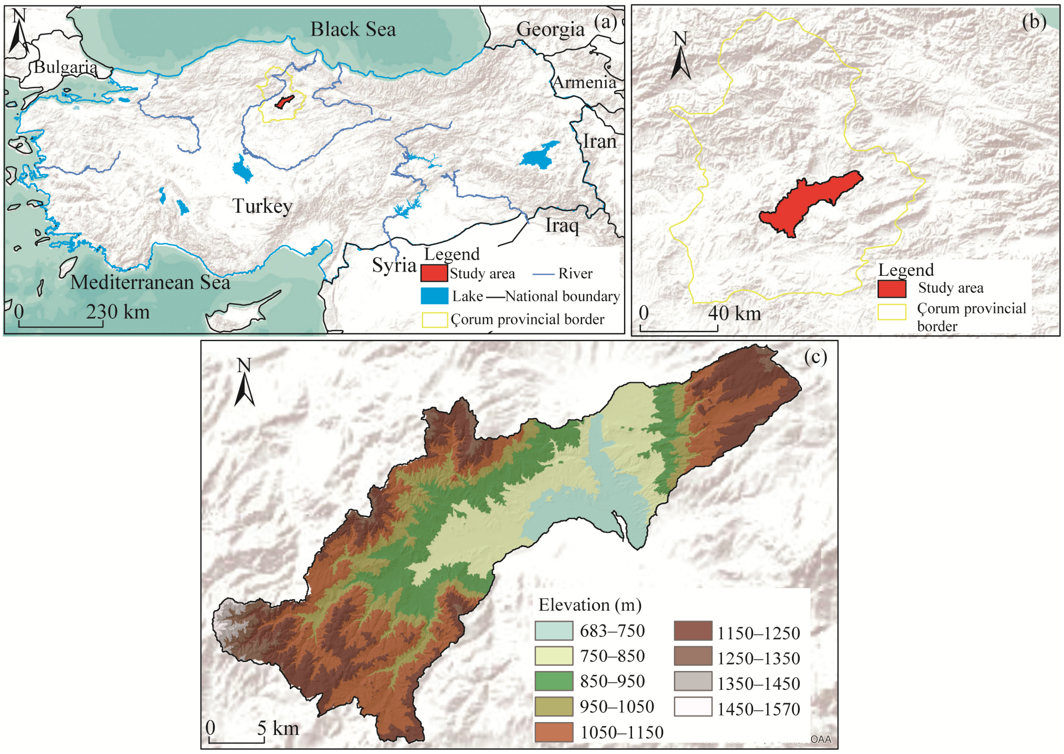

Fig. 1 Location (a and b) and elevation (c) of the study area

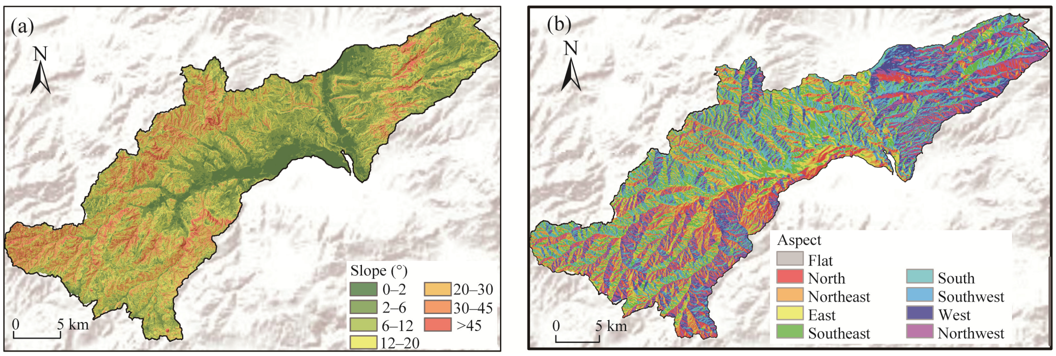

Fig. 2 Slope (a) and aspect (b) of the study area

Table 1 Distribution of land use/land cover in the Çorum Basin, Central Trukey

Land use/land cover	Area (km²)	Percentage (%)	Land use/land cover	Area (km²)	Percentage (%)
Continuous urban fabric	6.0	0.9	Complex cultivation patterns	29.0	4.4
Discontinuous urban fabric	10.0	1.5	Lands principally occupied by agriculture with significant areas of natural vegetation	80.0	12.1
Industrial or commercial units	17.2	2.6	Broad-leaved forests	38.0	5.8
Mineral extraction sites	2.0	0.3	Coniferous forests	17.0	2.6
Dump sites	1.0	0.2	Mixed forests	12.0	1.8
Non-irrigated arable lands	187.0	28.3	Natural grasslands	39.0	5.9
Permanently irrigated arable lands	97.0	14.7	Transitional woodlands/shrublands	91.0	13.8
Vineyards	0.8	0.1	Sparsely vegetated areas	22.0	3.3
Fruits trees and berry plantations	3.0	0.5	Water bodies	1.0	0.2
Pastures	7.0	1.1	Total	660.0	100.0

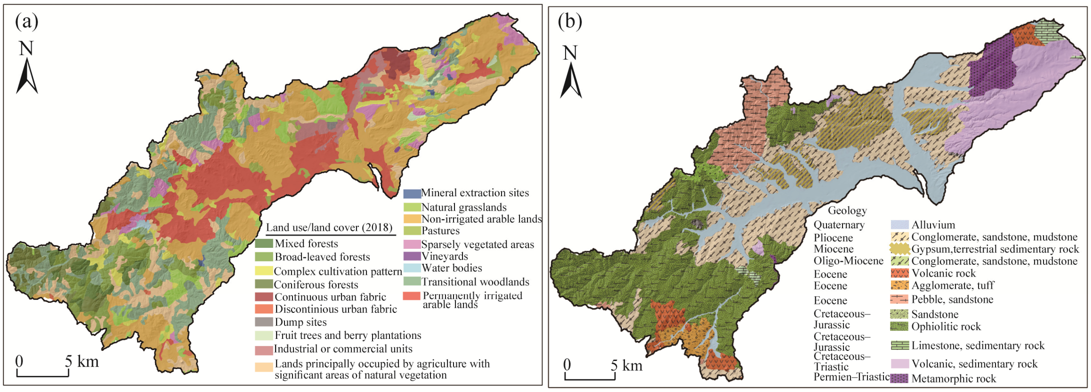

Fig. 3 Land use/land cover (a) and geology (b) of the study area

2.2 Assessment of SQI

We integrated the GIS (geographic information system) and RS (remote sensing) techniques with various methodologies, such as the best-worst method (BWM) and geostatistics, for the purpose of overcoming the complex ecological structure of nature. Hence, we developed a modeling architecture. Figure 4 shows the relationships between the methods used here. This soil quality study includes four steps. The first step constitutes the modeling structure and data collection for the database. The second step is choosing important and effective soil quality indicators. The third step is de-unitizing, scoring, and weighing the indicators and processing these data to acquire a spatial distribution for soil quality changes by means of GIS and validated satellite images. The final step is assessing the results acquired from data analysis.

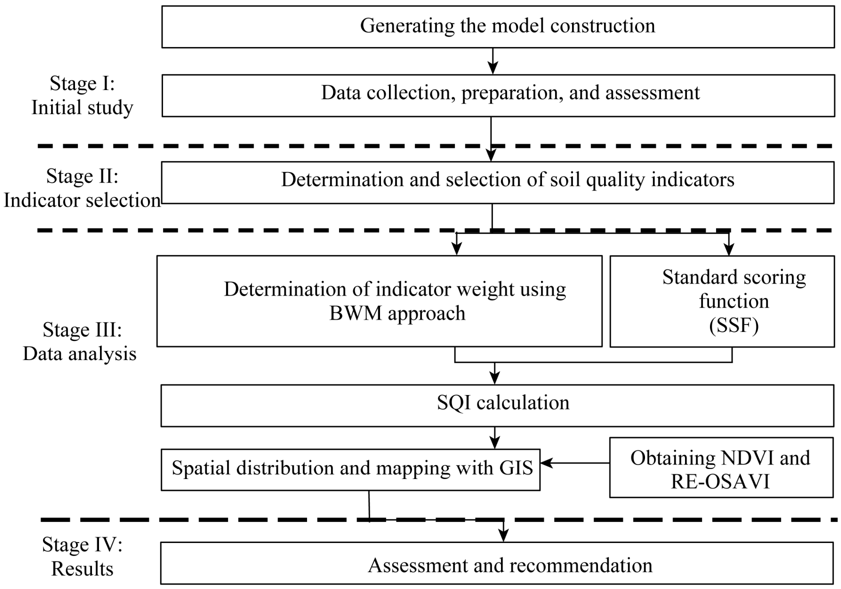

Fig. 4 Modelling architecture designed to determine SQI (soil quality index). BWM, best-worst method; GIS, geographic information system; NDVI, normalized difference vegetation index; RE-OSAVI, red-edge optimized soil-adjusted vegetation index.

2.3 Soil sampling and analysis

A total of 107 soil samples at the 20 cm soil depth were taken from the study area between September and October 2019 (Fig. 5). The collected soil samples were dried and sieved through a 2-mm sieve, and prepared for soil physical-chemical analysis in the laboratory. To calculate SQI

value, we performed texture analysis using the hydrometer method (Bouyoucos, 1951). $CaCO_3$ analysis was measured by the Scheibler's calcimeter (Soil Survey Staff, 1993). Soil pH was measured using a pH meter (Soil Survey Staff, 1992). Electrical conductivity (EC) was measured in saturated soil paste with a conductometer (Soil Survey Staff, 1992), and SOM content was determined by the Walkley-Black method modified by Jackson (1958). Furthermore, the slope parameter was determined from the 10 m resolution DEM (digital elevation model).

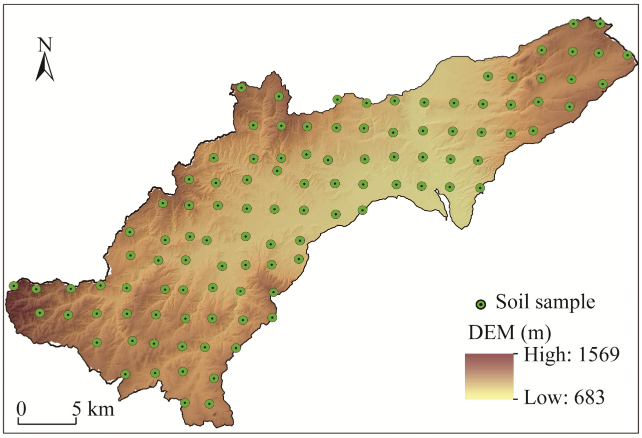

Fig. 5 Soil samples of the study area. DEM, digital elevation model.

2.4 Weighting model based on BWM

In BWM, the worst and best indicators are chosen, and each of these two indicators (worst and best) is compared with other factors in a paired format (Rezaei, 2015; Rezaei, 2016; Kalbasi et al., 2021). The steps of BWM are presented below (Rezaei, 2015; Rezaei, 2016):

Step 1: Making a set of choice indicators ($\{I_1, I_2, ..., I_n\}$ for n chosen indicators).

Step 2: Identifying the best-worst indicators based on decision-makers' preferences.

Step 3: Giving a value between 1 and 9 to define the relative importance of the best indication for all other indicators. The detailed calculation of BWM could be found in Rezaei (2016).

2.5 Standard scoring function

Different soil indicators are evaluated together when calculating SQI. In the current research, the nine physical and chemical soil indicators were considered for soil quality assessment. In order to select these soil indicators, we performed literature review with concerning previous soil quality studies (Demirağ Turan et al., 2019; Santos-Francés et al., 2019; Karaca et al., 2021; Kaya et al., 2022; Martin sanz et al., 2022; Samaei et al., 2022). Due to the large variety of units for the parameters, the standard scoring function (SSF) (Andrews et al., 2004) was employed for the unitization process, and scores varying between 0 and 1 were assigned. We divided two categories of criteria according to the degree of relationship with soil quality, with low and high values representing the most desired soil function (Liebig et al., 2001). First, clay, SOM, and soil depth were connected to the "more is better" function (MB). Second, for their roles in the deterioration of soils, the "less is better" (LB) function was linked to EC, $CaCO_3$, pH, sand, silt, and slope. Table 2 provides SSF equations (Andrews et al., 2004) for the indicators.

2.6 Determination of SQI and spatial distribution

SQI was mapped with the weighted linear combination (WLC) approach after the significance values of the parameters were established. Simple additive weighting (SAW), weighted summation, weighted linear average, and weighted overlay are other names for WLC (Malczewski and Rinner, 2015). Using WLC approach, SQI values are calculated by the following equation:

Table 2 Standard scoring functions (SSF) for soil parameters

Parameter	FT	L	U	SSF equation
pH	LB	6.90	8.56	
$CaCO_3$	LB	0.54	43.97	
Silt	LB	4.45	70.67	$f(x)=\begin{cases}0.1 & x\le L\\ 1-0.9\times\dfrac{x-L}{U-L}+0.1, & L\le x\le U\\ 1 & x\ge U\end{cases}$
Sand	LB	14.67	80.41	
Slope	LB	2.00	30.00	
EC	LB	0.04	1.55	
SOM	MB	0.45	6.31	
Clay	MB	5.63	63.98	$f(x)=\begin{cases}0.1 & x\le L\\ 0.9\times\dfrac{x-L}{U-L}+0.1, & L\le x\le U\\ 1 & x\ge U\end{cases}$
Depth	MB	20.00	120.00	

Note: FT, function type; LB, low is better; MB, more is better; SOM, soil organic matter. In equations, x is the monitoring value of the indicator; $f(x)$ is the score of indicators ranged between 0.1 and 1.0, and L and U are the lower and the upper threshold values, respectively.

$$\mathrm{SQI}_i=\sum_{k=1}^{l} w_k a_{ik}, \tag{1}$$

where SQI_i is the soil quality index value of region i; w_k is the relative importance level of the parameter and standard value of region a_{ik} under parameter k; and l is the total number of parameters (Elalfy et al., 2010).

The distribution maps of soil parameters and soil quality for the research area were created using interpolation model. Interpolation model is employed to map distance-dependent changes and point data (Goovaerts, 1998; Mulla and McBratney, 2000). In determining spatial distribution, inverse distance weighting (IDW), one of the most widely used interpolation models, universal and simple kriging methods, and radial basis function (RBF) were used in this study. Root mean square error (RMSE) and mean absolute error (MAE) are used to test the correlation.

$$\mathrm{RMSE}=\sqrt{\frac{\sum\left(z_{i^*}-z_i\right)^2}{n}}, \tag{2}$$

where Z_i is the estimated value; z_{i^*} is the observed value; and n is the number of observation.

2.7 Vegetation indices for biomass reflectance

Generally, NDVI is the most commonly used (Matton et al., 2005; Skakun et al., 2018), which has the value range from –1.0 to 1.0 (Salinas-Zavala et al., 2002; Al-Bakri and Suleiman, 2004; Pettorelli et al., 2005; Jiang et al., 2021). On this scale, water bodies are represented by NDVI values close to –1.0, while settlements, bare ground, rocky terrain, sand, and snow are represented by values close to 0.0. NDVI values close to 1.0 denote the presence of temperate zones, tropical rainforests, or regions with healthy and dense vegetation, and NDVI values between 0.2 and 0.4 correlate to areas of scrub or grasslands. NDVI is estimated by the following equation:

$$\mathrm{NDVI}=(\mathrm{NIR}-\mathrm{RED})/(\mathrm{NIR}+\mathrm{RED}), \tag{3}$$

where NIR is the near infrared band of 842 nm; RED is the red band of 665 nm.

RE-OSAVI represents an updated version of SAVI (soil-adjusted vegetation index) and was developed by Rondeaux et al. (1996). To reduce the effect of reduced mass on the red wavelength spectrum reflections, we modified the model as the optimized SAVI (OSAVI) model (RE-OSAVI) by adding the red edge (705 nm) band rather than the red band (670 nm) and making it more sensitive to the green field. According to the reports, this metric can be helpful, especially when vegetation density is low (Wu et al., 2008). The following formula is used for RE-OSAVI:

$$\text{RE-OSAVI}=(1+0.16)\times[(\mathrm{NIR}-\mathrm{REdge})/(\mathrm{NIR}+\mathrm{REdge}+0.16)], \tag{4}$$

where REdge is the band of 690–730 nm.

After the soil quality was assessed, ESA-SNAP (European Space Agency-SeNtinel Application Platform) v.8.0 was considered to calculate vegetation indices (NDVI and RE-OSAVI) from Sentinel-2A satellite images and to determine their relationship with vegetation.

3 Results

3.1 Physical and chemical properties of soils

The physical-chemical properties of the soil samples taken from the basin displayed variation in consequence of dynamic interactions among natural environmental factors, such as the degree of soil formation, leaching process, and agricultural activities, e.g., tillage systems or fertilization. Table 3 showed the soil physical-chemical properties and SQI values. SOM values ranged from 0.45% to 6.31%, whereas soil pH values varied from 6.90 to 8.56. The soil clay, silt, and sand contents varied between 5.63%–63.98%, 4.45%–70.67%, and 14.67%–80.41%, respectively. Skewness is the measure of symmetric distribution. If the distribution is long-tailed to the right, it is defined as positively skewed (i.e., right-skewed), and if it is long-tailed to the left, it is called negatively skewed (i.e., left-skewed). Kurtosis refers to the sharpness or roundness of the normal distribution curve, while SOM, depth, clay, sand, and SQI values are normally distributed, and other properties are not. The pH is left-skewed, whereas $CaCO_3$, EC, silt, and slope values are right-skewed. There are three levels of coefficient of variation: low (15%), medium (15%–35%), and high (>35%) according to its values. Accordingly, SOM, pH, EC, and SQI values were found to be of low variability, whereas slope was found to be of medium variability, and other characteristics were found to be of high variability.

Table 3 Statistics of soil physical-chemical parameters and SQI

Parameter	Max	Min	Mean	SD	CV	Variance (Dime)	Skewness (Dime)	Kurtosis (Dime)
SOM (%)	6.31	0.45	2.78	1.23	5.86	1.52	0.34	–0.32
pH	8.56	6.90	7.94	0.37	1.66	0.14	–0.77	–0.00
$CaCO_3$ (%)	43.97	0.54	10.04	8.27	43.43	68.39	1.53	3.23
EC (dS/m)	1.55	0.04	0.24	0.29	1.51	0.08	3.20	10.83
Depth (cm)	120.00	20.00	78.59	35.70	100.00	1280.09	–0.18	–1.38
Clay (%)	63.98	5.63	30.32	13.52	58.35	182.89	0.18	–0.85
Silt (%)	70.67	4.45	25.08	9.97	66.22	99.54	1.77	4.94
Sand (%)	80.41	14.67	44.59	14.42	65.74	208.10	0.18	–0.59
Slope (°)	45.00	2.00	15.10	9.14	28.00	83.71	0.42	–0.99
SQI	0.86	0.31	0.59	0.13	0.55	0.01	–0.15	–1.10

Note: SOM, soil organic matter; EC, electrical conductivity; SQI, soil quality index; SD, standard deviation; Min, minimum; Max, maximum; CV, coefficient of variation; Dime, dimensionless.

3.2 Interpolation models of soil chemical-physical properties

Spatial distribution for SQI was utilized with the aim of identifying the best predictive model from among fifteen semi-variogram models (IDW with the weights of 1, 2, and 3, RBF with thin plate spline (TPS), completely regularized spline (CRS) and spline with tension, simple kriging, ordinary kriging, universal kriging with spherical, exponential, and gaussian semivariograms). The models were tested, and then the variogram or function of every interpolation model giving the best results was identified, and RMSE values are presented in Table 4. Additionally, Figure 6 showed their spatial distribution maps. According to Table 4, the exponential semi-variogram of ordinary kriging is revealed to be the most suitable model for the spatial distribution of SOM, whereas the Gaussian method of simple kriging was selected as the most suitable semi-variogram model in creating the spatial distribution map of soil reaction in the study area due to the lowest RMSE value (pH, 0.371). As for other soil chemical properties, the Gaussian semi-variogram

model of simple kriging was found to be appropriate for the $CaCO_3$ distribution of soils as in the case of pH, while the Gaussian semi-variogram of ordinary kriging was determined as the most appropriate model for the spatial distribution of EC values of the soils.

Concerning the distribution of soil physical properties such as soil depth, texture (clay, silt, and sand), and slope, while IDW-2 method was found to be the most appropriate model for obtaining the distribution map of the soil depth parameter in the study area, the RMSE value of IDW-1 was detected as the lowest value for producing a clay distribution map. In the sand distribution, CRS method of RBF was also found to be the most appropriate model, and the sand content was lower in flat areas and higher in the surrounding mountainous areas. Finally, IDW-2 method was determined for silt distribution, and low values were identified in the remaining areas, except for a small area in the north of the study area.

Table 4 Interpolation models and RMSE values of soil quality criteria

Interpolation model	Semi-variogram model		Soil quality criteria								
			SOM (%)	pH	$CaCO_3$ (%)	EC (dS/m)	Depth (cm)	Clay (%)	Silt (%)	Sand (%)	Slope (°)
Inverse distance weighting (IDW)	IDW-1		1.214	0.383	7.322	0.264	0.549	0.554	0.990	0.921	0.728
	IDW-2		1.218	0.389	7.323	0.269	0.540	0.669	0.904	0.903	0.788
	IDW-3		1.243	0.398	7.408	0.279	0.559	0.710	0.990	0.960	0.789
Radial basis functions	TPS		1.348	0.475	9.101	0.338	0.610	0.711	0.998	0.998	0.880
	CRS		1.219	0.392	7.365	0.270	0.612	0.660	0.992	0.872	0.750
	SWT		1.216	0.389	7.334	0.267	0.611	0.566	0.990	0.879	0.765
Kriging	Ordinary	Gaussian	1.201	0.381	7.288	0.254	0.610	0.674	0.946	0.883	0.838
		Exponential	1.196	0.383	7.290	0.258	0.610	0.786	0.945	0.882	0.832
		Spherical	1.200	0.382	7.269	0.256	0.610	0.753	0.946	0.883	0.831
	Simple	Gaussian	1.188	0.371	7.251	0.257	0.612	0.649	0.947	0.885	0.830
		Exponential	1.186	0.374	7.372	0.267	0.613	0.662	0.947	0.884	0.831
		Spherical	1.188	0.374	7.256	0.257	0.612	0.661	0.948	0.885	0.831
	Universal	Gaussian	1.201	0.381	7.288	0.254	0.611	0.671	0.948	0.886	0.832
		Exponential	1.196	0.383	7.290	0.258	0.612	0.671	0.946	0.886	0.832
		Spherical	1.200	0.382	7.269	0.256	0.613	0.672	0.947	0.887	0.833

Note: RMSE, root mean square error; TPS, thin plate spline; CRS, completely regularized spline; SWT, spline with tension; SOM, soil organic matter; EC, electrical conductivity.

3.3 Evaluation of soil quality and spatial distribution

The current work used 9 parameters in SQI assessment for desertification and land degradation. To create an appropriate SQI value for every soil sample, we considered BWM approach to assign appropriate weight values to each parameter. Among the soil indicators considered in terms of desertification and land degradation, soil depth was evaluated as the best parameter, and sand was evaluated as the worst parameter due to its direct effects, such as water and nutrient retention and root development. Tables 5 and 6 showed the preference matrices. We calculated the optimal weights according to Rezaei (2015, 2016). ξ^{L*} (i.e., the parameter that used in BWM for measuring the model's consistency) value was found to be 0.123. According to BWM, results are considered more consistent if the value is close to zero (Rezaei, 2016). According to BWM, depth (0.2817) is the most important parameter, followed by slope (0.2024), SOM (0.1349), clay (0.1012), pH (0.0809), EC (0.0674), silt (0.0578), $CaCO_3$ (0.0506), and sand (0.0226).

Score values were determined for all indicators by evaluating the best soil quality impacts integrated with high, low, or medium (optimal range) values varying between 0 and 1 for each parameter. Finally, after determining the scores for each parameter value and weighting each

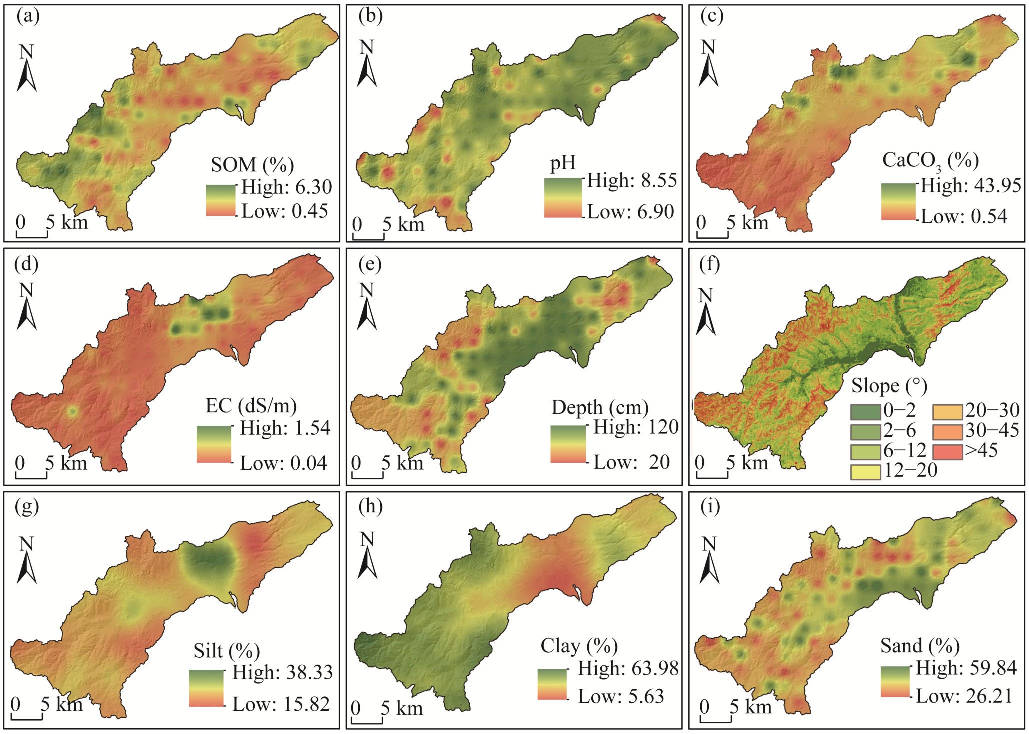

Fig. 6 Distribution maps of the soil quality criteria. (a), soil organic matter (SOM); (b), pH; (c), $CaCO_3$; (d), electrical conductivity (EC); (e), soil depth; (f), slope; (g), silt; (h), clay; (i), sand.

Table 5 Pairwise comparison vector for the best criterion

Best to others	Depth	Slope	SOM	Clay	pH	EC	Silt	$CaCO_3$	Sand
Depth	1	2	3	4	5	6	7	8	9

Table 6 Pairwise comparison vector for the worst criterion

Others to the worst	Depth	Slope	SOM	Clay	pH	EC	Silt	$CaCO_3$	Sand
Sand	7	4	3	5	8	6	8	2	1

parameter according to BWM, we considered a weighted linear combination technique to estimate SQI for every soil sample. Additionally, the spatial distribution of SQI obtained for each soil sample was done using interpolation models. The most appropriate RMSE value was selected, and a soil quality distribution map was created in the study area (Fig. 6). To create the spatial distribution map of SQI, we determined the most appropriate interpolation model to be the simple exponential kriging model (Fig. 7).

3.4 Relationship between biomass reflectance values and SQI

In the study, R^2 values of the statistical correlation between SQI and NDVI of Sentinel-2A satellite images dated May, June, July, and August 2021 with different time series were determined as 0.802, 0.724, 0.694, and 0.631, respectively (Fig. 8). The months with the highest R^2 values were May and June. It can be noted that there is a parallel between the high vegetation density in these months and the distribution pattern of SQI. We found that there was a low distribution in soil quality in the slope lands where NDVI values were low in the basin.

RE-OSAVI approach was also used in the current study to increase the support for the relationship between soil quality and biomass reflectance. SQI and RE-OSAVI values derived from Sentinel-2A satellite images dated May, June, July, and August 2021 with various time series and R^2 values of the statistical relationship between them were determined as 0.795, 0.685, 0.647, and 0.631, respectively (Fig. 9).

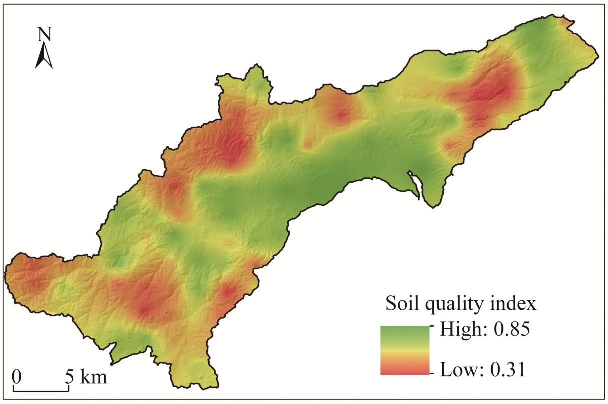

Fig. 7 Spatial distribution map of soil quality index in the study area

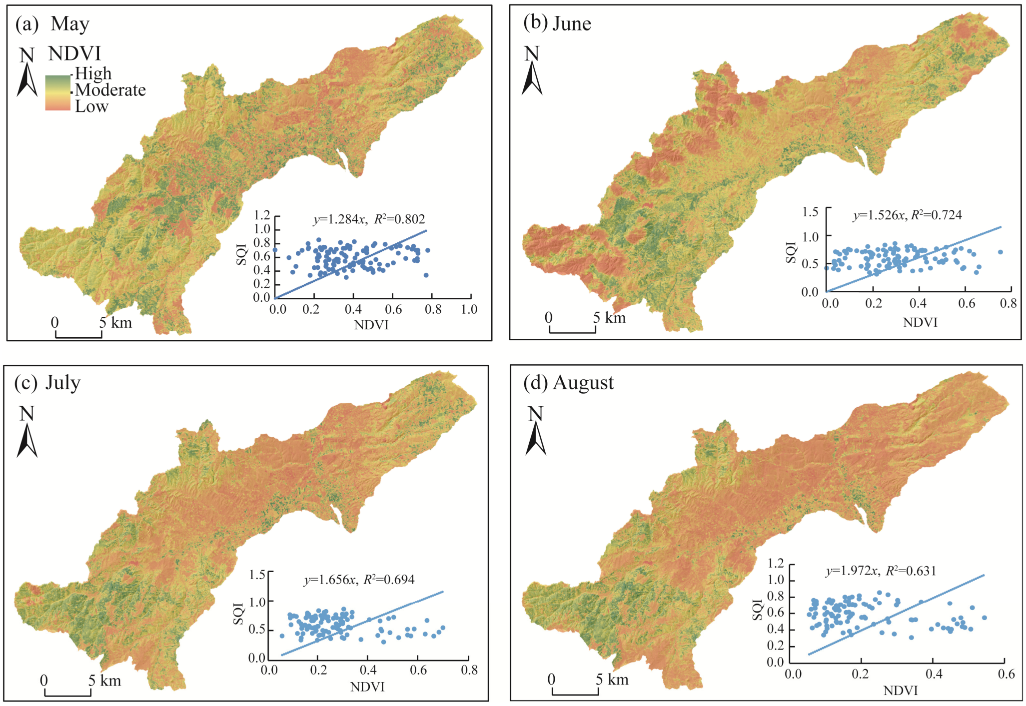

Fig. 8 R^2 values between soil quality index (SQI) values and NDVI (normalized difference vegetation index) values with different time series. (a), May; (b), June; (c), July; (d), August.

4 Discussion

4.1 Spatial distribution of selected soil quality indicators

A significant step in the sustainability process for SQI in arid and semi-arid soils is to select appropriate indicators. The common soil physical indicators employed in the current research involve surface soil particle size distribution (clay, silt, and sand) and soil depth (Rahmanipour et al., 2014; Ahmed et al., 2016; Dedeoğlu and Dengiz, 2019; Kaya et al., 2022). Furthermore, the study area includes steep hillsides and receives irregularly distributed annual precipitation. Hence, the mentioned areas have a potentially high risk of soil erosion due to low vegetation cover. Therefore, the slope factor or topographic features are important elements for evaluating land degradation and desertification. Moreover, the chemical characteristics of the soil are crucial to determine the amount of yield, plant health, the health of biomass developing, and land productivity dynamics.

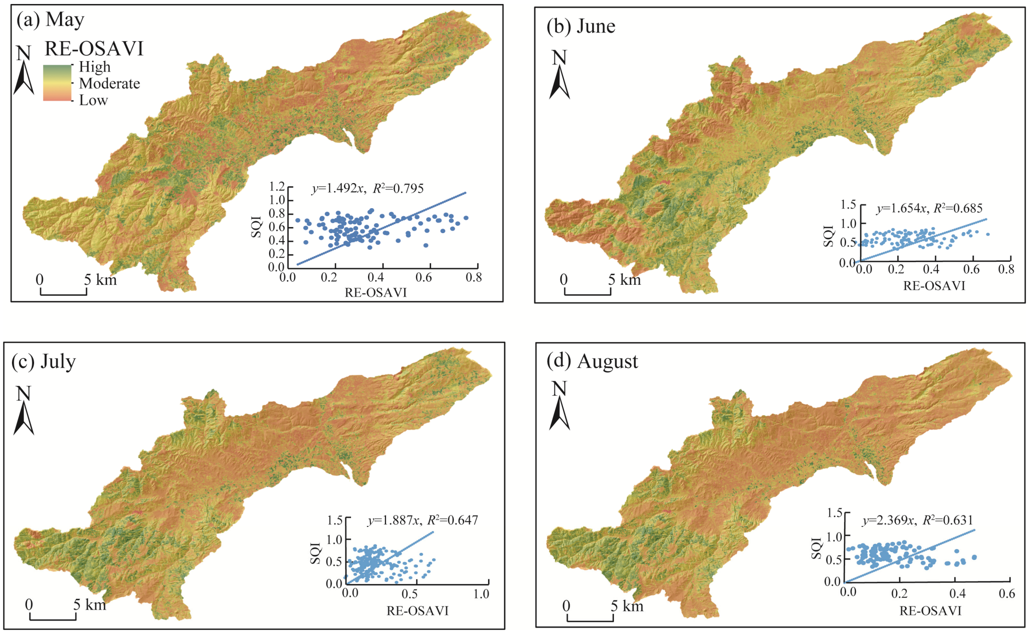

Fig. 9 R^2 values between soil quality index (SQI) values and RE-OSAVI (red-edge optimized soil-adjusted vegetation index) values with different time series. (a), May; (b), June; (c), July; (d), August.

The following soil characteristics ($CaCO_3$, SOM, pH, and EC) have been suggested by numerous researchers because of their impacts on root development, soil structure, the availability of nutrient elements, soil pore size, soil fertility, aggregate stability, etc. (Chen et al., 2013; Jiang et al., 2017; Nabiollahi et al., 2017). On the other hand, no consensus has been reached either on which soil properties should be considered for soil quality monitoring or on how the criteria should be interpreted (Schipper and Sparling, 2000). Likewise, Qi et al. (2009) reported that the absence of a widely accepted method or approach for creating SQI was among the most restricting factors in soil quality assessment. For example, sodium concentration was utilized as an indicator by Andrews et al. (2004), which was uncommon in earlier studies. In addition to this example, indicators employed by Qi et al. (2009) involved drainage parameters not present in any other approach and the hard pan layer in profile in addition to standard indicators. Since soil quality represents a complicated notion and various site-specific soil conditions are needed for different purposes of land use, this lack of unanimity can partly be attributed to these factors (Karaca et al., 2021). Therefore, it is impossible to employ numerous factors that affect soil quality at different levels. Hence, it is crucial to choose the right indicators for soil quality assessment. Doran and Parkin (1996) and Karaca et al. (2021) found that using as few factors as possible was recommended when determining soil quality.

Demirağ Turan et al. (2019) and Karaca et al. (2021) reported that SOM content was a crucial measure of soil quality for both agricultural (i.e., production and economy) and environmental (i.e., the health of environment, carbon sequestration, productivity dynamics, and air quality) activities. Within the basin, the amount of SOM is high in the mountainous areas in the west and southwest of the study area, while it is low in the central parts of the area where agricultural activities are intensively carried out. This causes the spatial distribution of SOM in the basin to be quite high. The most important reason for this fluctuation is that there are especially forests and pastures that are a source of SOM on the slope lands situated in the southwestern parts of the catchment, whereas SOM is reduced due to a high oxidation process after soil cultivation or intensive agricultural activities in the central parts of the catchment.

While pH of the high values distributed in the south and southwest of the study area exhibits slightly acidic characteristics due to the fact that these areas receive a little more precipitation,

which may cause the leaching of basic cations from the soil, and the presence of volcanic rocks in these areas. Soil pH values are, in general, high and show alkaline reaction due to geological materials such as limestone and marl rocks. This case also affects $CaCO_3$ content of soils. $CaCO_3$ values are low, especially in the southern parts of the study area, due to the effect of volcanic rocks not producing carbonate. Moreover, Eyüpoğlu (1999) also studied $CaCO_3$ content of the soils in Turkey and found that 58.6% of the soils were calcareous because of parent material (i.e., marl and limestone) and low precipitation, mostly in the Central Anatolia region. Costantini et al. (2016) indicated that salinity and alkalinity of the soils were prevalent in arid and semi-arid areas, particularly in agricultural lands using inappropriate irrigation techniques. Furthermore, it was revealed that there was no salinity problem in the soils of the study area, and spatial variability of EC values was generally low.

In arid and semi-arid areas, soil depth is among the most significant soil criteria because it takes a key part in the retention and regulation of useful water and nutrients, which directly or indirectly affects the development of soil flora and fauna in accordance with the physical-chemical and morphological properties of the soils. Ozsahin et al. (2017) and Demirağ Turan et al. (2019) indicated that soil depth was one of the main indicators of desertification and land degradation, referring to a thickness up to the lower boundary where soil formation process ends. While deep soils in the study area with the less slope of the basin and a shallow soil depths in the basin are found in the surrounding mountainous areas, especially due to erosion.

Furthermore, soil particle size significantly impacts soil drainage, water-holding capacity, soil erosion, soil air, and temperature circulation, as well as soil fertility and plant productivity. Clay, which directs the important physical-chemical properties of soils, is generally distributed at low levels due to erosion in areas with a high slope and poor vegetation cover in the basin, while the clay amount increases in flat and gently sloping lands where the slope is less. The reverse situation can be observed in the distribution of sand within the basin.

4.2 Multi-criteria assessment and weighting values

The goal of employing a multi-indicator model with BWM is to identify answers to decision-making issues characterized by various choices that can be evaluated using decision criteria. SQI, such as soil depth, soil texture, SOM, pH, EC, $CaCO_3$, their properties, and weighting rates are normally used to compile information on the study area. This study found the highest value (0.269) for soil depth, while the lowest value (0.042) was revealed for sand content. The above-mentioned results are also in line with many other investigations. For example, Shulka et al. (2006) carried out a factor analysis for soil quality, and soil depth was one of the five factors they identified. Mijangos and Garbisu (2010) determined soil quality according to soil properties at different depths and emphasized that soil quality characteristics changed according to depth, while Kaya et al. (2022) considered soil depth as an effective parameter of soil quality and determined soil depth as the highest value after erosion among all of parameters.

In our study, the second highest weighting value (0.139) was found for SOM. It is well known that SOM is a key indicator of soil quality, both for agricultural and environmental functions. Furthermore, SOM represents a primary factor influencing physical-chemical and biological soil properties. Samaei et al. (2022) determined soil quality in pasture and agricultural lands in northwestern Iran on the basis of the total and minimum datasets. They concluded that clay and pH, among the parameters used in this study, should be used instead of the total dataset. Moreover, SOM, EC, pH, and $CaCO_3$ used in this study are among the parameters employed in soil quality studies in terms of affecting soil productivity (Chen et al., 2013; Jiang et al., 2017; Nabiollahi et al., 2017; Karaca et al., 2021; Mirghaed and Souri, 2022; Taghipour et al., 2022). Finally, according to BWM, we estimated the weighting values of silt, sand, $CaCO_3$, and EC to be below 10%, demonstrating the generally uniform distribution of these indicators in the basin.

4.3 Distribution of SQI with validated biomass reflectance values

After BWM process was conducted to obtain the weighting values for each soil quality parameter,

we applied a weighted linear combination approach to estimate SQI by considering the score of each quality criterion. According to SQI distribution map, soil quality values are high in flat and gently sloping areas with a high clay content and soil depth, which are generally distributed in the central parts of the basin, while soil quality values are low especially in areas with a high slope, poor vegetation cover, and sandy texture. These factors and conditions cause soil erosion, low soil fertility and water holding capacity, low soil productivity dynamics, and high desertification risk. SQI distribution was also supported by biomass reflectance values of satellite images from different months in 2021. The red and near-infrared parts of the spectrum have been recognized as particularly beneficial for monitoring agroecosystems (Xie et al., 2018). Biomass reflectance values of plants and spectral index models have been utilized for monitoring soil quality in various land management practices (Gupta et al., 2003; Zand and Matinfar, 2012; Dedeoglu et al., 2020). Upon analyzing the correlations between SQI and vegetation indices in our study, we found the highest relationships in both NDVI and RE-OSAVI in May and June. In other words, the low SQI values of sloping lands with a high slope and shallow soil depth may cause low vegetation index values. Concerning soil quality, it is necessary to follow vegetation periods because one of the main objectives of studies focusing on soil quality is to estimate soil productivity. Additionally, when we compared the two vegetation indices, we concluded that NDVI had the highest relationship with R^2 values of 0.802 in May. Likewise, Karaca et al. (2021) analyzed the relationship between SQI of pasture lands in a semi-arid ecosystem and RE-OSAVI values, included red-edge and NIR bands, derived from Sentinel-2A satellite images dated May, June, and July 2019 by conducting linear regression analysis. In line with the analysis results, R^2 values between SQI and RE-OSAVI in May, June, and July were 0.760, 0.800, and 0.520, respectively. The researchers found the strong correlation between soil quality and biomass reflectance, especially for June.

5 Conclusions

In the present study, soil quality was analyzed in terms of desertified and degraded Çorum Basin, Central Turkey, and the correlation of RE-OSAVI and NDVI produced from Sentinel-2A satellite images for various time series with soil quality was tested. Initially, SQI was developed by firstly assessing physical and chemical parameters to cope with heterogenic ecological conditions in the study area by using weighted linear combination technique. In addition to that, BWM and SSF approaches were also used to supply a mathematical strength to capture the uncertainties associated with human cognitive process by integrating with GIS and RS techniques to contribute soil quality within the semi-arid ecosystems. In the study, based on the distribution of soil quality map, we found that the soils distributed in the middle parts of the study area as well as the soils distributed in the slope areas with less vegetation cover showed a higher soil quality distribution. Therefore, pasture and forest rehabilitation measures should be carried out to ensure that these areas are covered by vegetation to reduce soil transport by erosion, and SOM level should be increased to ensure a strong aggregation of the soils. Moreover, soil quality map was compared with vegetation indices extracted from satellite images. SQI showed statistically significant relationship with NDVI in May. In conclusion, the method used and the results obtained will contribute to planning sustainable soil management strategies for researchers. Moreover, it is suggested that increasing the number of biophysical parameters (aggregate stability, permeability, cation exchange capacity, etc.) in SQI determination and adding land management practices will improve the accuracy of future studies.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions

Conceptualization: Orhan DENGİZ, İnci DEMİRAĞ TURAN; Methodology: Orhan DENGİZ, İnci DEMİRAĞ TURAN; Formal analysis: Orhan DENGİZ, İnci DEMİRAĞ TURAN; Writing - original draft preparation: Orhan DENGİZ, İnci DEMİRAĞ TURAN; Writing - review and editing: Orhan DENGİZ, İnci DEMİRAĞ TURAN.

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